Improving $PM_{2.5}$ Estimation from Satellite Aerosol Optical Depth Using Boundary Layer Height and Meteorological Variables

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***Abstract*—Accurate estimation of surface particulate matter ($PM_{2.5}$) from satellite observations remains challenging because aerosol optical depth (AOD) represents column-integrated aerosol loading and is strongly influenced by meteorological conditions. This study investigates the relationship between satellite-derived AOD, meteorological variables, and surface $PM_{2.5}$ concentrations over Mumbai, India, during the period 2021–2025.**

A total of 1,248 collocated observations of $PM_{2.5}$, AOD, boundary layer height (BLH), relative humidity (RH), temperature, wind parameters, and solar radiation were analyzed. Several physically informed predictor variables were developed to account for atmospheric mixing and humidity effects, including a humidity- and boundary-layer-corrected aerosol indicator (AOD_DRY_BLH). Linear regression and Random Forest models were subsequently evaluated using statistical validation, seasonal analysis, temporal analysis, and error assessment.

Raw AOD exhibited a weak relationship with $PM_{2.5}$ ($r = 0.270$, $R^2 = 0.073$), whereas the engineered variable AOD_DRY_BLH increased explanatory power by approximately 4.3 times relative to raw AOD ($r^* = 0.562$, $R^2 = 0.316$). Boundary layer height emerged as the strongest controlling factor, followed by relative humidity and atmospheric dryness. The best-performing linear model achieved a test-set R^2 of 0.449, while the Random Forest model yielded a test-set R^2 of 0.667 with lower prediction errors (MAE = 12.00 μg m^{-3}; RMSE = 16.49 μg m^{-3}) than the best-performing linear formulation. Temporal validation demonstrated relatively stable performance across the study period, whereas seasonal analysis revealed stronger predictive skill during the pre-monsoon season and reduced performance during winter and monsoon conditions.

The results demonstrate that incorporating meteorological constraints significantly improves the capability of satellite-derived aerosol observations to represent surface $PM_{2.5}$ concentrations. The findings highlight the dominant influence of atmospheric mixing and humidity on aerosol–$PM_{2.5}$ relationships and support the integration of physically informed variables with machine learning approaches for urban air-quality assessment in tropical environments.

***Index Terms*—$PM_{2.5}$, Aerosol Optical Depth, Boundary Layer Height, Air Quality, Remote Sensing, Random Forest, Mumbai**

I. Introduction

Fine particulate matter ($PM_{2.5}$) is among the most important atmospheric pollutants affecting human health, visibility, and regional climate [1][2]. Long-term exposure to elevated $PM_{2.5}$ concentrations has been associated with increased risks of respiratory illness, cardiovascular disease, and premature mortality [3][4]. Consequently, accurate monitoring of $PM_{2.5}$ remains a critical component of air-quality management and environmental policy.

Ground-based monitoring networks provide highly accurate measurements of surface particulate matter; however, their spatial coverage is often limited, particularly in rapidly developing urban regions. Satellite remote sensing offers an attractive complementary approach by providing consistent, large-scale observations of atmospheric aerosols [5][6][7]. Aerosol Optical Depth (AOD), a measure of total column aerosol loading, has therefore been widely used as a proxy for surface $PM_{2.5}$ concentrations [5][6][7][8].

Despite extensive application, the relationship between satellite-derived AOD and surface $PM_{2.5}$ remains highly variable across locations, seasons, and atmospheric conditions [5][9][10]. Numerous studies have demonstrated that AOD alone frequently explains only a limited fraction of $PM_{2.5}$ variability because it represents the integrated aerosol burden throughout the atmospheric column rather than concentrations near the surface [5][10][11]. As a result, identical AOD values may correspond to substantially different surface $PM_{2.5}$ concentrations depending on meteorological and atmospheric conditions. Recent literature consistently identifies relative humidity, boundary layer height, atmospheric stability, wind conditions, land-surface characteristics, and topographic influences as major controls governing the strength of satellite–ground pollutant relationships [12][13][14][15].

Among these factors, atmospheric mixing processes and humidity effects are particularly important. Boundary layer height regulates the vertical dilution of pollutants, while relative humidity modifies aerosol optical properties through hygroscopic growth [15]. These processes can substantially alter the correspondence between column-integrated aerosol observations and surface particulate matter concentrations. Previous studies have shown that incorporating meteorological information significantly improves $PM_{2.5}$ estimation accuracy compared with the use of satellite observations alone [9][12][11][16]. Furthermore, advanced machine learning approaches frequently outperform traditional linear models by capturing nonlinear interactions between atmospheric variables [17][18][19].

Mumbai represents a particularly challenging environment for satellite-based air-quality assessment. As a densely populated coastal megacity, the city experiences strong seasonal variability driven by monsoon circulation, changing boundary layer dynamics, marine influences, and intense anthropogenic emissions. These interacting processes create substantial temporal variability in the $PM_{2.5}$–AOD relationship and provide an ideal setting for investigating the environmental controls governing satellite–ground air-quality correspondence [20].

While many previous studies have focused primarily on improving $PM_{2.5}$ prediction accuracy, fewer investigations have explicitly examined why satellite-derived aerosol observations succeed or fail under different atmospheric conditions. Recent research has emphasized the need to move beyond purely predictive frameworks and instead investigate the environmental mechanisms controlling satellite–surface relationships [11][16].

Therefore, the objective of this study is not only to evaluate the capability of satellite-derived AOD to estimate surface $PM_{2.5}$ concentrations over Mumbai during 2021–2025, but also to identify the atmospheric factors responsible for variations in model performance. Specifically, this study (i) quantifies relationships between $PM_{2.5}$ and satellite-derived aerosol observations, (ii) investigates the influence of boundary layer height and meteorological conditions on these relationships, (iii) develops physically informed predictor variables incorporating atmospheric mixing and humidity effects, (iv) compares linear regression and machine learning approaches, and (v) evaluates model robustness through seasonal, temporal, and cross-validation analyses. The findings contribute to a broader understanding of how environmental processes influence the reliability of satellite-based $PM_{2.5}$ estimation in complex tropical urban environments [11].

II. Study Area and Data

A. Study Area

Mumbai, India, was selected as the study area due to its status as one of the world's largest coastal megacities and its persistent air-quality challenges. Located along the western coast of India (approximately 18.9°N–19.3°N, 72.7°E–73.1°E), Mumbai experiences a tropical climate characterized by distinct winter, pre-monsoon, monsoon, and post-monsoon seasons.

The city's atmospheric environment is influenced by a combination of anthropogenic emissions, coastal meteorology, and seasonal monsoon dynamics. Major emission sources include vehicular traffic, industrial activities, construction processes, residential fuel combustion, and port-related operations. In addition, seasonal changes in boundary-layer dynamics, humidity, rainfall, and wind patterns strongly affect pollutant accumulation and dispersion.

These characteristics make Mumbai an ideal natural laboratory for investigating the environmental controls governing satellite-derived aerosol observations and ground-level particulate matter concentrations [20]. The spatial extent analyzed in this study is shown in (Fig. 1).

Fig. 1. Study area and region of interest (ROI) used for Aerosol Optical Depth (AOD) and Boundary Layer Height (BLH) extraction over Mumbai, India. The red rectangle denotes the spatial extent analyzed in Google Earth Engine (72.75°E–72.98°E, 18.85°N–19.30°N) during 2021–2025.

B. Ground-Based $PM_{2.5}$ Data

Ground-level $PM_{2.5}$ observations were obtained from the Central Pollution Control Board (CPCB) air-quality monitoring network [21]. Hourly $PM_{2.5}$ measurements spanning January 2021 to December 2025 were collected and subjected to quality-control procedures prior to analysis.

To ensure temporal consistency with satellite observations and meteorological datasets, hourly $PM_{2.5}$ measurements were aggregated to daily mean concentrations. Records containing missing values or physically unrealistic measurements were excluded during preprocessing. The resulting daily $PM_{2.5}$ dataset served as the target variable throughout model development and validation.

C. Satellite-Derived Aerosol and Boundary Layer Data

Satellite-derived Aerosol Optical Depth (AOD) and Boundary Layer Height (BLH) observations were obtained through the Google Earth Engine (GEE) platform for the Mumbai metropolitan region bounded by 72.75°E–72.98°E and 18.85°N–19.30°N [22].

AOD observations were retrieved from the MODIS Multi-Angle Implementation of Atmospheric Correction (MAIAC) product (MCD19A2 Version 6.1), using the Optical_Depth_055 band [23]. Daily mean AOD values were computed by spatially averaging all valid retrievals within the study region. AOD represents the total column-integrated aerosol loading and is widely employed as a satellite-derived indicator of atmospheric particulate abundance.

Boundary Layer Height data were obtained from the ECMWF ERA5 Hourly reanalysis dataset available within GEE [24]. Hourly BLH observations were spatially averaged over the study area and subsequently aggregated to daily statistics. Two boundary-layer metrics were considered:

- Daily mean Boundary Layer Height (BLH)
- Daily maximum Boundary Layer Height (BLH_MAX)

where BLH_MAX represents the maximum hourly boundary-layer height observed during a given day.

The inclusion of BLH was motivated by its fundamental role in regulating atmospheric dilution and vertical mixing processes [25][26]. Lower boundary-layer heights typically constrain pollutant dispersion, whereas deeper boundary layers enhance atmospheric ventilation and reduce near-surface pollutant accumulation [26][27].

All satellite-derived and reanalysis-based observations were temporally aligned with corresponding CPCB observations prior to model development.

D. Feature Engineering

To incorporate physically meaningful atmospheric processes governing aerosol accumulation, transport, and dispersion, a suite of derived predictor variables was constructed.

The influence of vertical dilution on the satellite–surface aerosol relationship was represented through the AOD–BLH interaction term:

$$AOD\_BLH = AOD/BLH$$

To account for the influence of atmospheric moisture on aerosol optical properties, a humidity-adjusted aerosol indicator was defined as:

$$AOD\_DRY = \frac{AOD}{1 + RH/100}$$

The humidity-adjusted aerosol indicator was introduced to partially account for aerosol hygroscopic growth under humid atmospheric conditions. Elevated relative humidity can increase aerosol optical depth through water uptake by hygroscopic particles, thereby enhancing optical extinction without a proportional increase in dry particulate mass concentration [15][28]. The AOD_DRY formulation provides a simple first-order correction intended to reduce humidity-induced inflation of AOD values and improve correspondence with ground-level $PM_{2.5}$ concentrations.

A combined aerosol–humidity–mixing predictor was subsequently developed as:

$$AOD\_DRY\_BLH = \frac{AOD\_DRY}{BLH}$$

A dryness index was additionally computed as:

$$DRYNESS = 100 - RH$$

To characterize directional transport processes, wind direction was transformed into orthogonal vector components:

$$WD\_sin = \sin(WD)$$

$$WD\_cos = \cos(WD)$$

A Ventilation Coefficient (VC) was also calculated to represent the atmosphere's capacity to disperse pollutants inspired from the model defined in [29]:

$$VC = BLH \times WS$$

where BLH denotes the daily mean boundary-layer height and WS represents daily mean wind speed. Higher ventilation coefficients indicate enhanced atmospheric dispersion conditions, while lower values favor pollutant accumulation.

These engineered variables were designed to explicitly incorporate the physical mechanisms responsible for observed discrepancies between columnar aerosol loading and ground-level $PM_{2.5}$ concentrations.

E. Final Dataset

Following preprocessing, quality control, temporal matching, and feature engineering, the final dataset consisted of 1,248 quality-controlled daily observations and 21 predictor variables covering the period 2021–2025.

The resulting dataset provided a comprehensive representation of aerosol loading, meteorological conditions, atmospheric mixing processes, and seasonal variability for subsequent statistical and machine-learning analyses.

III. Methodology

A. Overall Analytical Framework

The methodological workflow was designed to investigate the relationship between satellite-derived aerosol loading and ground-level $PM_{2.5}$ concentrations in Mumbai while accounting for the influence of atmospheric mixing, humidity, and meteorological variability.

The analysis consisted of four sequential phases:

1) Development of a multi-source daily air-quality dataset integrating ground observations, satellite observations, and atmospheric reanalysis products.
2) Construction of physically informed aerosol correction variables designed to account for boundary-layer dilution and hygroscopic effects.
3) Development and comparison of statistical and machine-learning models for $PM_{2.5}$ estimation.
4) Comprehensive model validation through train–test evaluation, cross-validation, temporal assessment, seasonal analysis, and residual diagnostics.

A schematic overview of the methodological workflow is presented in (Fig. 2).

B. Data Integration and Preprocessing

Hourly $PM_{2.5}$ and meteorological observations obtained from the CPCB monitoring network were aggregated to daily mean values. Meteorological variables included relative humidity (RH), air temperature (AT), wind speed (WS), wind direction (WD), and solar radiation (SR) [21].

Hourly Boundary Layer Height (BLH) observations extracted from the ERA5 Hourly reanalysis dataset were spatially averaged over the study area and aggregated to daily statistics. Both daily mean BLH and daily maximum BLH (BLH_MAX) were retained for analysis [24].

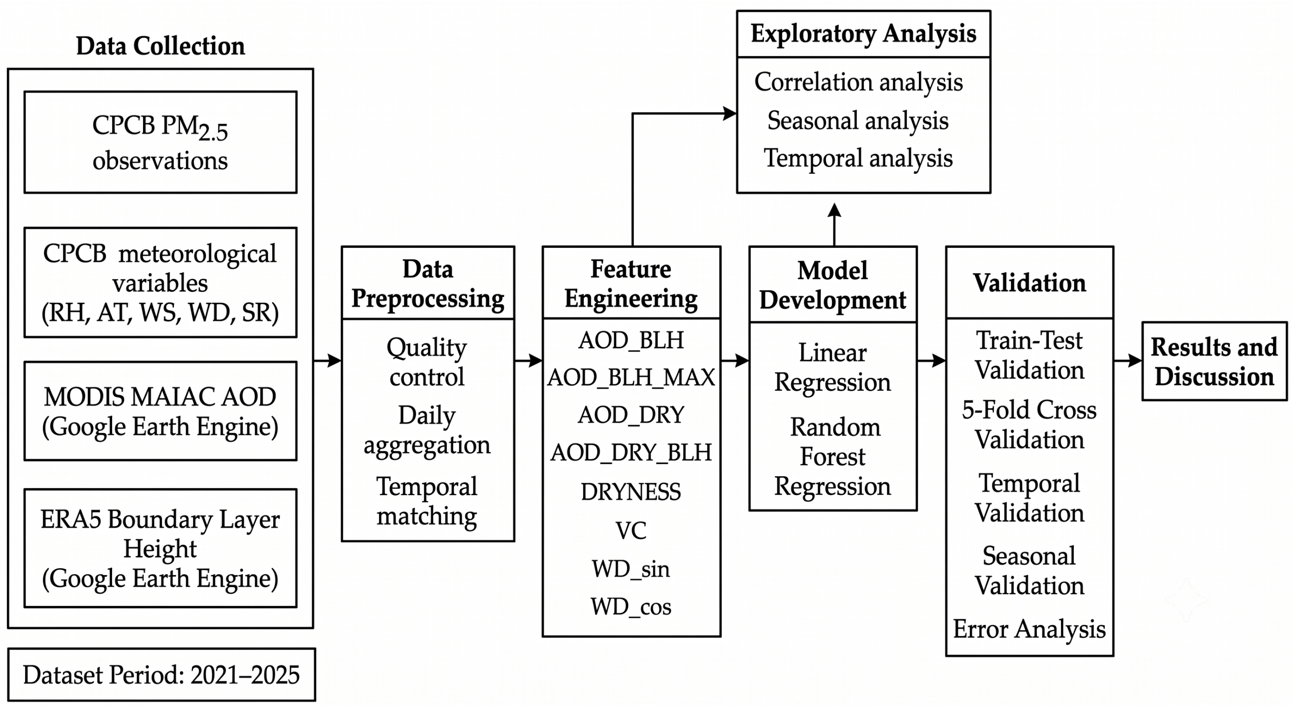


Fig. 2. Overall methodological workflow adopted for $PM_{2.5}$ estimation, including data collection, preprocessing, feature engineering, exploratory analysis, model development, validation, and interpretation.

Daily MODIS MAIAC AOD retrievals were extracted from Google Earth Engine and spatially averaged over the study region [23].

All datasets were temporally matched using observation date and merged into a unified analytical database. Records containing missing values in key predictor variables were removed prior to modelling.

Following quality control and temporal harmonization, the final dataset consisted of 1,248 daily observations spanning January 2021–December 2025.

C. Feature Engineering

To improve the physical representation of aerosol processes, several derived variables were developed.

1) Boundary-Layer Correction: To account for atmospheric dilution effects, an AOD–BLH interaction term was calculated using the model defined in [13]:

$$AOD\_BLH = (AOD/BLH)$$

An alternative formulation using daily maximum boundary-layer height was also evaluated:

$$AOD\_BLH\_MAX = AOD/BLH\_MAX$$

2) Humidity Adjustment: Because aerosol optical properties are strongly influenced by hygroscopic growth under humid conditions, a humidity-adjusted aerosol indicator was defined as:

$$AOD\_DRY = AOD/(1 + RH/100)$$

This correction was designed to reduce the influence of aerosol hygroscopic growth on satellite-derived aerosol optical depth. Under high-humidity conditions, aerosols absorb atmospheric moisture and exhibit enhanced optical scattering, causing AOD to increase even when dry particulate mass remains relatively unchanged. Dividing AOD by a relative-humidity-dependent factor provides an approximate adjustment for this effect and yields a predictor more closely related to surface particulate concentrations [13].

A combined aerosol–humidity–mixing indicator was subsequently developed [13]:

$$AOD\_DRY\_BLH = \frac{AOD\_DRY}{BLH}$$

Although the exact formulation differs from previous studies, the predictor was inspired by established approaches that incorporate humidity and boundary-layer corrections into AOD-based $PM_{2.5}$ estimation models [13].

3) Atmospheric Ventilation Metrics: A Ventilation Coefficient (VC) was calculated as [29]:

$$VC = BLH \times WS$$

where WS denotes daily mean wind speed.

A dryness index was also computed:

$$DRYNESS = 100 - RH$$

4) Wind Direction Encoding: To avoid discontinuities associated with circular wind-direction measurements, wind direction was transformed into orthogonal vector components:

$$WD\_sin = \sin(WD)$$

$$WD\_cos = \cos(WD)$$

These derived variables were intended to represent atmospheric mixing, pollutant dispersion, moisture effects, and directional transport processes that influence the relationship between columnar aerosol loading and surface $PM_{2.5}$ concentrations.

D. Exploratory Statistical Analysis

Initial analysis consisted of Pearson correlation calculations between $PM_{2.5}$ and all predictor variables.

Correlation matrices were generated to examine inter-variable relationships and identify potential multicollinearity among predictors.

Temporal analyses were additionally conducted on annual and seasonal subsets to investigate variability in the $PM_{2.5}$–AOD relationship under different atmospheric regimes.

E. Regression Model Development

A hierarchy of linear regression models was developed to quantify the incremental contribution of physically informed predictors.

The evaluated model configurations included:

1) Model A:

$$PM_{2.5} = f(AOD)$$

2) Model B:

$$PM_{2.5} = f(AOD\_BLH)$$

3) Model C:

$$PM_{2.5} = f(AOD\_DRY\_BLH)$$

4) Model D:

$$PM_{2.5} = f(AOD\_DRY\_BLH, RH)$$

5) Model E:

$$PM_{2.5} = f(AOD\_DRY\_BLH, RH, WS)$$

6) Model F:

$$PM_{2.5} = f(AOD\_DRY\_BLH, RH, WS, WD\_sin, WD\_cos).$$

Model performance was quantified using the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Additional benchmark models incorporating raw AOD, BLH, and meteorological variables were also evaluated to quantify the incremental contribution of engineered predictors.

F. Random Forest Modelling

To investigate nonlinear relationships between atmospheric variables and $PM_{2.5}$ concentrations, a Random Forest regression model was implemented.

Random Forest was selected due to its ability to capture nonlinear interactions among aerosol loading, humidity, and atmospheric mixing variables.

The Random Forest model incorporated all available aerosol, meteorological, boundary-layer, and engineered variables.

Model hyperparameters included:

- Number of trees = 500
- Maximum tree depth = 10
- Random state = 42

Feature-importance scores derived from the Random Forest model were used to identify the dominant predictors governing $PM_{2.5}$ variability.

G. Model Validation

1) Train–Test Validation: For all predictive models, the dataset was randomly divided into training (80%) and testing (20%) subsets.

Model performance was evaluated using:

- Coefficient of Determination (R^2)
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)

Differences between training and testing performance were used to assess model generalization and potential overfitting.

2) K-Fold Cross-Validation: The best-performing linear model was further evaluated using five-fold cross-validation.

The dataset was partitioned into five mutually exclusive subsets. During each iteration, four subsets were used for model training and the remaining subset was reserved for validation.

The mean and standard deviation of validation R^2 values were used as indicators of model robustness.

3) Temporal Validation: To evaluate temporal stability, annual validation analyses were conducted separately for 2021–2025.

Pearson correlation coefficients between observed $PM_{2.5}$ concentrations and model predictors were calculated for each year.

4) Seasonal Validation: Season-specific validation analyses were performed for:

- Winter
- Pre-Monsoon
- Monsoon
- Post-Monsoon

Seasonal correlation statistics were used to evaluate the influence of differing meteorological conditions on model performance.

H. Error Analysis

Residual analysis was conducted to identify systematic prediction errors and model limitations. Absolute prediction errors were calculated for all observations, and seasonal error

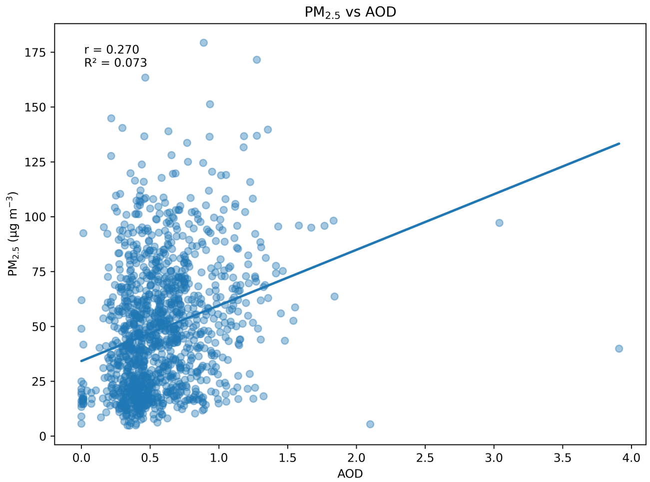


Fig. 3. Relationship between satellite-derived Aerosol Optical Depth (AOD) and observed $PM_{2.5}$ concentrations. The weak correlation highlights limitations of using uncorrected column-integrated aerosol measurements as a proxy for surface particulate matter.

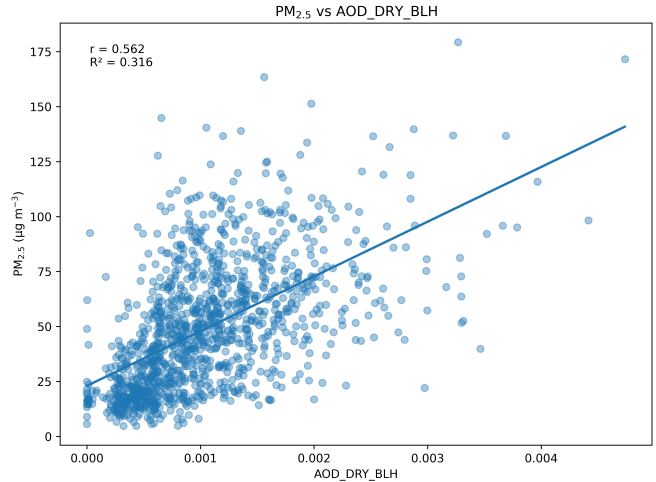


Fig. 4. Relationship between observed $PM_{2.5}$ concentrations and the humidity- and boundary-layer-corrected aerosol indicator AOD_DRY_BLH. The physically informed predictor exhibits a substantially stronger association with $PM_{2.5}$ than uncorrected AOD.

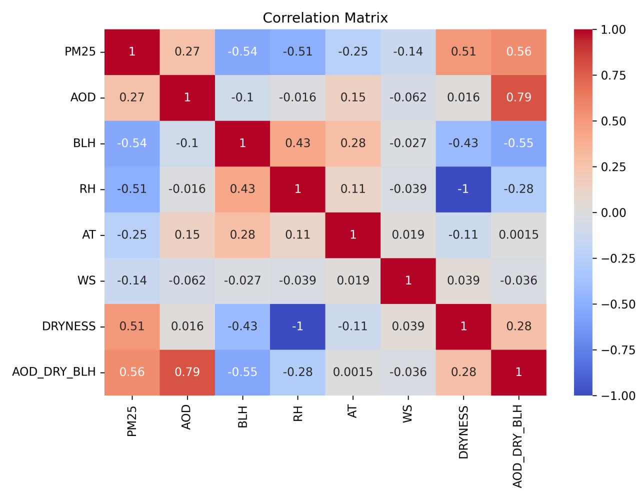
statistics were derived to evaluate performance under different atmospheric conditions. Residual distributions were examined to identify systematic prediction biases and extreme prediction errors. This analysis provided additional insight into the strengths and limitations of physically informed $PM_{2.5}$ estimation approaches in a tropical coastal megacity environment.

IV. Results

A. $PM_{2.5}$–AOD Relationship

A total of 1,248 collocated observations of $PM_{2.5}$, aerosol optical depth (AOD), boundary layer height (BLH), and meteorological parameters were obtained for Mumbai during 2021–2025. The direct relationship between surface $PM_{2.5}$ concentration and raw AOD was weak, yielding a correlation coefficient of $r = 0.270$ and a coefficient of determination of $R^2 = 0.073$ (Fig. 3). Considerable scatter was observed across the full range of $PM_{2.5}$ concentrations, indicating that column-integrated aerosol loading alone provides limited representation of near-surface particulate matter variability.

To account for atmospheric mixing and humidity effects, a series of physically informed predictor variables were constructed. Among these, the combined variable AOD_DRY_BLH exhibited the strongest individual relationship with $PM_{2.5}$ ($r = 0.562$, $R^2 = 0.316$), representing a substantial improvement over the uncorrected AOD product (Fig. 4).



	PM25	AOD	BLH	RH	AT	WS	DRYNESS	AOD_DRY_BLH
PM25	1	0.27	-0.54	-0.51	-0.25	-0.14	0.51	0.56
AOD	0.27	1	-0.1	-0.016	0.15	-0.062	0.016	0.79
BLH	-0.54	-0.1	1	0.43	0.28	-0.027	-0.43	-0.55
RH	-0.51	-0.016	0.43	1	0.11	-0.039	-1	-0.28
AT	-0.25	0.15	0.28	0.11	1	0.019	-0.11	0.0015
WS	-0.14	-0.062	-0.027	-0.039	0.019	1	0.039	-0.036
DRYNESS	0.51	0.016	-0.43	-1	-0.11	0.039	1	0.28
AOD_DRY_BLH	0.56	0.79	-0.55	-0.28	0.0015	-0.036	0.28	1

Fig. 5. Correlation matrix illustrating relationships among $PM_{2.5}$ concentrations, aerosol indicators, meteorological variables, and engineered predictors. Strong dependencies highlight the importance of atmospheric mixing and humidity effects.

B. Influence of Meteorological Parameters

Correlation analysis identified BLH as the strongest individual predictor of $PM_{2.5}$ ($r = -0.544$), followed by relative humidity ($r = -0.507$) and the dryness parameter ($r = 0.507$). Atmospheric temperature, wind speed, solar radiation, ventilation coefficient, and wind-direction components exhibited comparatively weaker individual associations. The strongest engineered predictors were AOD_DRY_BLH ($R^2 = 0.316$) and AOD_BLH ($R^2 = 0.259$), both outperforming raw AOD.

These results demonstrate that incorporating meteorological constraints substantially enhances the statistical relationship between satellite-derived aerosol observations and surface particulate concentrations. The correlation structure among $PM_{2.5}$, aerosol indicators, meteorological variables, and engineered predictors is shown in (Fig. 5).

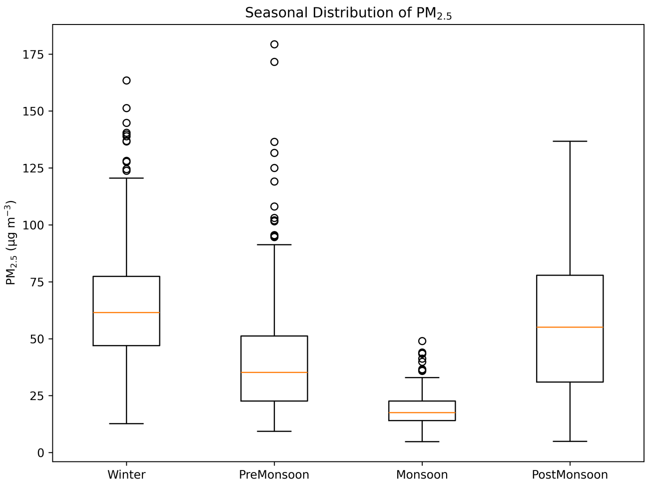


Fig. 6. Seasonal distribution of daily $PM_{2.5}$ concentrations across Mumbai during 2021–2025. Winter and post-monsoon periods exhibit elevated particulate matter levels relative to monsoon conditions.

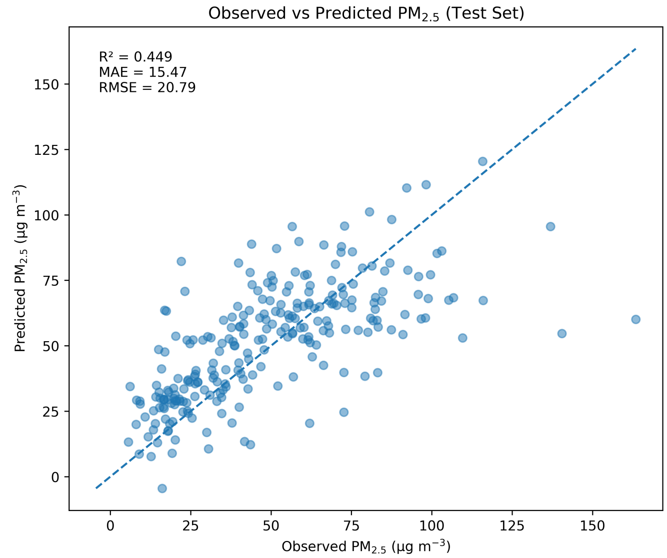


Fig. 7. Comparison of observed and linear-regression-predicted $PM_{2.5}$ concentrations for the independent test dataset. The close agreement indicates strong predictive performance and model generalization capability.

C. Regression Model Performance

The baseline linear model incorporating AOD and BLH achieved an R^2 of 0.343. The inclusion of additional meteorological variables increased model performance. Among the benchmark formulations, the model incorporating AOD, BLH, RH, wind speed, and temperature achieved an $R^2 = 0.514$. A sequence of engineered-variable regression models was subsequently evaluated. Model F, consisting of AOD_DRY_BLH, relative humidity (RH), wind speed (WS), and wind-direction components (WD_sin and WD_cos), achieved the highest predictive performance among all linear formulations, yielding a test-set R^2 of 0.449, a mean absolute error (MAE) of 15.47 μg m^{-3}, and a root mean square error (RMSE) of 20.79 μg m^{-3}. The agreement between observed and predicted $PM_{2.5}$ concentrations is illustrated in (Fig. 7).

To evaluate model robustness beyond a single train–test split, the best-performing linear regression model (Model F) was further assessed using five-fold cross-validation. Validation R^2 values ranged from 0.449 to 0.548, with a mean R^2 of 0.492 and a standard deviation of 0.036 (Fig. 9). The relatively small variation across folds indicates stable predictive performance and suggests that model skill was not strongly dependent on a specific partitioning of the dataset.

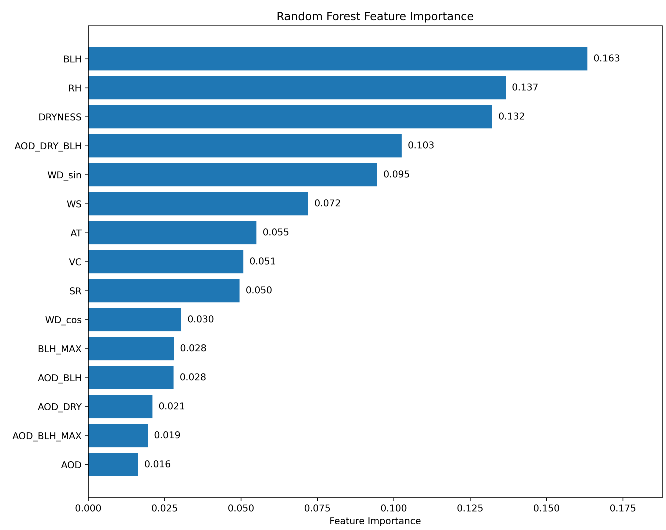


Fig. 8. Random Forest feature-importance rankings for $PM_{2.5}$ estimation. Boundary Layer Height (BLH), atmospheric dryness, and relative humidity emerged as the dominant predictors controlling model performance.

D. Random Forest Modelling

The Random Forest model achieved the highest predictive skill among all tested approaches, with training and test coefficients of determination of 0.920 and 0.667, respectively. Corresponding test-set errors were MAE = 12.00 μg m^{-3} and RMSE = 16.49 μg m^{-3}. Feature-importance analysis revealed BLH as the dominant predictor, followed by dryness, relative humidity, and AOD_DRY_BLH (Fig. 8). Raw AOD exhibited the lowest relative importance among the evaluated variables.

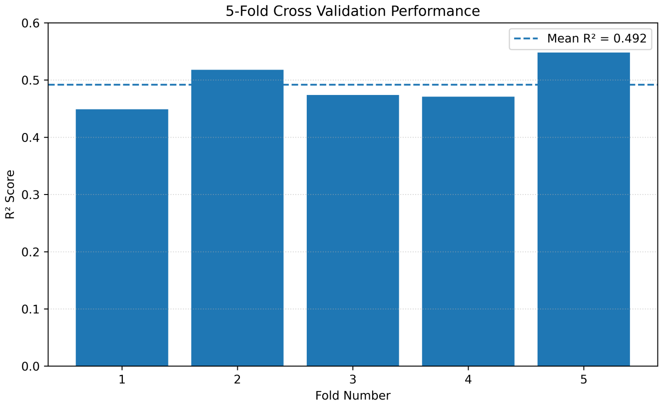


Fig. 9. Five-fold cross-validation performance of the best-performing linear regression model (Model F). Validation R^2 values remained relatively consistent across folds (mean R^2 = 0.492 ± 0.036), indicating stable predictive performance and limited sensitivity to dataset partitioning.

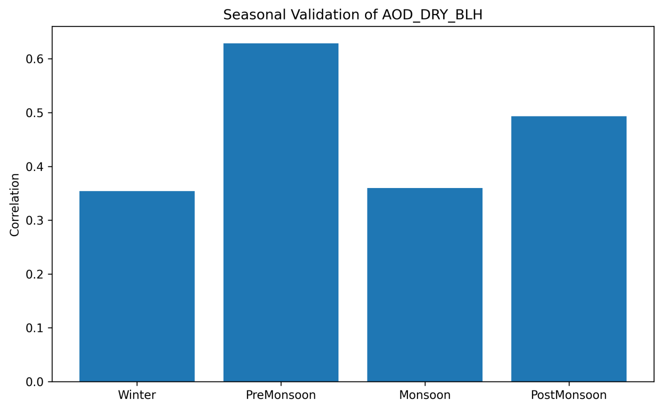


Fig. 10. Season-specific correlations between observed $PM_{2.5}$ concentrations and the AOD_DRY_BLH predictor. Predictive skill was highest during the pre-monsoon period and lowest during winter and monsoon conditions.

E. Temporal and Seasonal Evaluation

Temporal validation indicated relatively consistent model behavior across the study period. Annual correlation coefficients ranged from 0.426 to 0.624, with the highest performance observed in 2023 and the lowest in 2025 (Fig. 11). The reduced performance observed in 2025 may reflect incomplete annual sampling coverage and changing atmospheric conditions during the study period. Seasonal evaluation revealed substantial variability in predictive skill [20][30]. The strongest performance occurred during the pre-monsoon season (r = 0.629), followed by post-monsoon conditions (r = 0.493). Lower correlations were observed during winter (r = 0.354) and monsoon (r = 0.360) periods (Fig. 10). Seasonal $PM_{2.5}$ distributions showed maximum concentrations during winter (64.57 μg m^{-3}) and minimum concentrations during the monsoon season (19.09 μg m^{-3}) (Fig. 6).

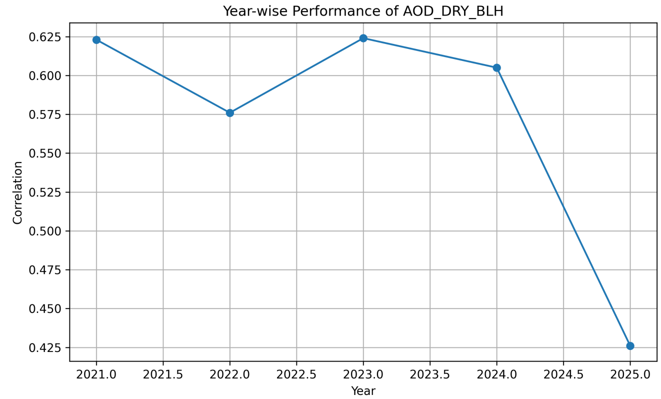


Fig. 11. Year-wise correlations between $PM_{2.5}$ concentrations and the AOD_DRY_BLH predictor (2021–2025), illustrating temporal robustness of the engineered aerosol indicator.

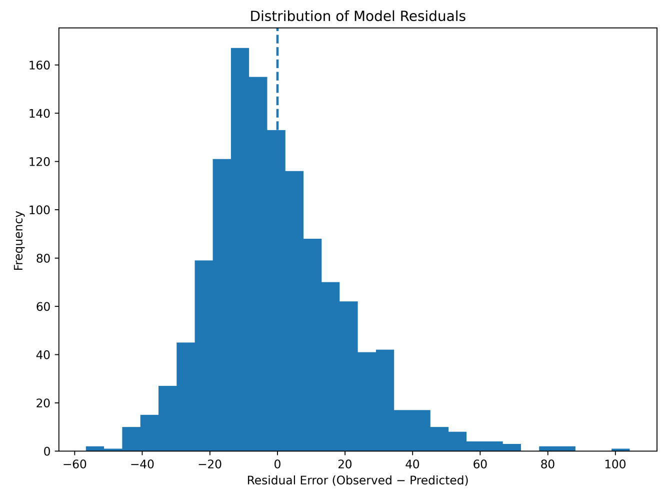


Fig. 12. Distribution of model residuals (observed minus predicted $PM_{2.5}$). Residuals are centered near zero, indicating limited systematic bias, while the positive tail reflects occasional underestimation of extreme pollution events.

F. Error Characteristics

The overall distribution of absolute prediction errors yielded a mean of 15.66 μg m^{-3} and a median of 12.54 μg m^{-3}. Seasonal error analysis indicated the lowest average errors during the monsoon season (10.76 μg m^{-3}) and the highest during winter (18.58 μg m^{-3}). Inspection of the largest residuals revealed that the most pronounced prediction errors were associated with extreme pollution episodes, where observed $PM_{2.5}$ concentrations exceeded approximately 100 μg m^{-3}. The ten largest residuals were predominantly associated with wintertime conditions. The distribution of model residuals is shown in (Fig. 12).

V. Discussion

A. Limitations of Raw AOD for Surface $PM_{2.5}$ Estimation

The weak relationship observed between raw AOD and surface $PM_{2.5}$ concentration highlights a fundamental limitation of satellite-based aerosol observations. Aerosol optical depth represents the vertically integrated aerosol burden throughout the atmospheric column, whereas $PM_{2.5}$ measurements reflect particulate concentrations near the surface. Consequently, variations in aerosol vertical distribution can substantially weaken the direct statistical relationship between the two variables [31].

The low predictive skill of raw AOD ($R^2 = 0.073$) indicates that aerosol loading alone is insufficient to represent day-to-day variations in surface air quality over Mumbai. Similar findings have been reported in numerous AOD–$PM_{2.5}$ studies, where meteorological conditions were shown to strongly modulate the translation of columnar aerosol abundance into near-surface particulate concentrations [9][12].

The substantial improvement achieved after incorporating boundary layer height and humidity corrections suggests that atmospheric structure exerts a dominant influence on the observed $PM_{2.5}$–AOD relationship [16].

B. Role of Boundary Layer Height

Boundary layer height emerged as one of the most influential predictor in both correlation analysis and Random Forest feature importance rankings [25][26]. The observed negative relationship between BLH and $PM_{2.5}$ is physically consistent with atmospheric dilution processes [9][12][25][26].

A shallow boundary layer restricts vertical mixing and confines pollutants within a smaller atmospheric volume, leading to elevated surface concentrations. Conversely, a deeper boundary layer promotes dispersion and dilution, reducing near-surface particulate accumulation.

The strong influence of BLH was further supported by the large difference in $PM_{2.5}$ concentrations observed between low-BLH and high-BLH conditions. This result suggests that atmospheric mixing processes may exert a greater control on $PM_{2.5}$ variability than aerosol loading alone within the study region [32].

These findings are particularly relevant for tropical urban environments, where seasonal variations in boundary layer development can significantly alter pollutant accumulation and dispersion mechanisms.

C. Importance of Humidity Correction

Relative humidity exhibited a strong negative association with $PM_{2.5}$ and was consistently identified as one of the most important predictor across all modelling approaches.

The humidity-corrected variable AOD_DRY_BLH substantially outperformed raw AOD, indicating that moisture-related effects influence the interpretation of satellite-derived aerosol observations. High humidity conditions can enhance aerosol hygroscopic growth, thereby increasing optical depth without a proportional increase in dry particulate mass concentration [28][33][34].

By partially accounting for humidity effects, the AOD_DRY_BLH formulation produced a stronger relationship with observed $PM_{2.5}$ [15][28]. The improvement suggests that physically informed corrections can reduce the discrepancy between optical measurements and surface mass concentrations.

The strong performance of the combined variable further demonstrates that AOD, boundary layer dynamics, and atmospheric moisture should be considered jointly rather than independently when estimating surface particulate matter.

D. Seasonal Variability in Model Performance

Substantial seasonal differences were observed in model performance. The strongest correlations occurred during the pre-monsoon season, whereas winter and monsoon periods exhibited considerably weaker relationships.

The enhanced pre-monsoon performance may be associated with relatively stable atmospheric conditions, stronger boundary layer development, and reduced cloud contamination compared with monsoon conditions. Under such circumstances, satellite-derived aerosol measurements may provide a more representative indication of near-surface particulate loading [35].

In contrast, the monsoon season is characterized by high humidity, extensive cloud cover, wet scavenging processes, and complex aerosol–meteorology interactions. These factors introduce additional uncertainty into both aerosol retrievals and $PM_{2.5}$ estimation, reducing predictive skill despite lower average pollution levels [16][36].

Winter conditions present a different challenge. Although $PM_{2.5}$ concentrations are highest during winter, the associated atmospheric environment is often dominated by stagnant conditions, shallow boundary layers, episodic pollution events, and enhanced local emissions. Such conditions can generate extreme $PM_{2.5}$ values that are difficult to capture using relatively simple predictor formulations [20][32].

The seasonal dependence observed in this study suggests that a single annual model may not fully represent all atmospheric regimes and that season-specific parameterizations may further improve predictive performance [11][16].

E. Advantages of Machine Learning Approaches

The Random Forest model achieved substantially higher predictive performance than all linear formulations, increasing test-set R^2 from 0.449 to 0.667 [18][37].

This improvement indicates the presence of nonlinear interactions among aerosol, meteorological, and atmospheric boundary layer variables [14][17][18]. Linear models assume fixed relationships between predictors and $PM_{2.5}$; however, atmospheric processes are inherently nonlinear and frequently involve threshold effects, seasonal dependencies, and variable interactions.

The Random Forest framework is capable of capturing such complexities without requiring explicit specification of interaction terms [38]. The resulting increase in predictive skill demonstrates that machine learning approaches can better represent the multi-factor controls governing $PM_{2.5}$ variability in urban environments [19][39].

Nevertheless, the persistence of prediction errors during extreme pollution episodes indicates that additional predictors, including emission inventories, transport indicators, or higher-resolution meteorological information, may be required to further improve model performance.

F. Implications for Urban Air Quality Monitoring

The results demonstrate that physically informed meteorological corrections substantially enhance the utility of satellite-derived aerosol observations for $PM_{2.5}$ estimation [14][16].

The superior performance of AOD_DRY_BLH compared with raw AOD suggests that simple corrections based on atmospheric physics can yield meaningful improvements even before the application of advanced machine learning techniques.

For rapidly urbanizing regions where ground-based monitoring networks remain sparse, the integration of satellite observations with meteorological information offers a promising framework for air-quality assessment. The findings further indicate that atmospheric mixing conditions and humidity effects should be explicitly incorporated into future $PM_{2.5}$ retrieval algorithms developed for tropical coastal megacities [8][40].

Overall, the study demonstrates that combining satellite aerosol products with meteorological constraints provides a more physically realistic representation of surface particulate matter than the use of AOD alone.

VI. Conclusion

This study investigated the relationship between satellite-derived aerosol optical depth (AOD), meteorological variables, and surface $PM_{2.5}$ concentrations over Mumbai during the period 2021–2025. A total of 1,248 collocated observations were analyzed to evaluate the effectiveness of physically informed predictor variables and machine learning approaches for $PM_{2.5}$ estimation.

The results demonstrated that raw AOD exhibited limited predictive capability for surface $PM_{2.5}$ concentrations, yielding a relatively weak correlation and low explanatory power. Incorporation of boundary layer height and humidity corrections substantially improved model performance, highlighting the importance of atmospheric mixing and moisture effects in controlling the $PM_{2.5}$–AOD relationship.

Among the engineered predictors, the humidity and boundary-layer-corrected variable AOD_DRY_BLH produced the strongest individual relationship with $PM_{2.5}$ and significantly outperformed uncorrected AOD. Boundary layer height emerged as the dominant controlling factor across both statistical and machine learning analyses, while relative humidity also exhibited a strong influence on particulate matter variability.

Linear regression models incorporating meteorological information achieved moderate predictive skill, whereas the Random Forest model provided the highest overall performance with a test-set coefficient of determination of 0.667. Feature-importance analysis further confirmed the dominant roles of boundary layer dynamics and atmospheric moisture in regulating near-surface particulate concentrations.

Temporal validation indicated relatively stable model behavior across multiple years, although seasonal performance varied substantially. The strongest predictive capability was observed during the pre-monsoon season, while winter and monsoon conditions remained more challenging due to complex atmospheric and aerosol processes.

Overall, the findings demonstrate that physically informed meteorological corrections significantly enhance the utility of satellite-derived aerosol observations for $PM_{2.5}$ estimation in tropical urban environments. Future work should investigate season-specific modelling strategies, incorporate additional predictors related to emissions and atmospheric transport, and evaluate higher-resolution satellite products to further improve predictive performance.

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Conflict of Interest

The author declares no conflict of interest.

Data Availability

The datasets used in this study are publicly available. Ground-based $PM_{2.5}$ observations were obtained from the Central Pollution Control Board (CPCB) air-quality monitoring network. MODIS MAIAC Aerosol Optical Depth (AOD) and ERA5 Boundary Layer Height (BLH) datasets were accessed through Google Earth Engine.

Ethics Statement

This study did not involve human participants, animals, or sensitive personal data. Ethical approval was therefore not required.

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